

Large-Scale Financial Forecasting Using Advanced GAI-based Large Language Models and Time Series Analysis

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Abstract—Financial forecasting has become a point of scrutiny with the development of AI and the increasing access to financial information but precise stock price prediction is hard because the market is volatile and nonlinear. This research paper provides a hybrid forecasting framework with past S&P 500 data (approximately 200,000 historical records) to assess machine-learning and sophisticated GAI-based deep-learning models. The methodology includes systematic data preprocessing, large-scale feature engineering, processing of missing and infinite values, and Min-Max normalization, followed by time-ordered data splitting for training and evaluation. XGBoost is used to model nonlinear relationships among structured financial data with time-series, and an ALBERT-based Transformer model is employed to capture long-range temporal dependencies using attention mechanisms. As can be seen in the experimental results, ALBERT has a higher performance with an R2 of 0.9930, RMSE of 4.3021, and MAE of 2.1380, which is significantly much higher than XGBoost and conventional deep learning models like LSTM, which has a higher error rate. The strength and precision of the ALBERT model in close correlation of actual price movements is proven by the comparative analysis. It is concluded that GAI-based Transformer models can be an effective and scalable solution to the needs of financial time series forecasting, though at the price of increased computational costs. This work demonstrates the practical applicability of lightweight Transformer architectures for accurate and data-driven financial decision-making systems.

Keywords—financial forecasting, time series analysis, LLM, feature engineering, financial data analytics.

I. INTRODUCTION

The ever-increasing complexity of financial markets has sparked an enormous need for advanced predictive analytics, as the daily trade volumes go into the billions of dollars [1]. Financial forecasting is a significant aspect of the modern finance field as it forms the basis of decision-making in different spheres of the economy [2], [3]. It covers a wide range of methodologies that predict the future market trends, prices of assets and economic indicators [4]. Accurate forecasting enables risk mitigation, informed investment planning, and improved portfolio management in highly volatile market environments. Financial markets operation and risk management cannot work without the forecasting of financial time series changes [5]. An example of the most traditional financial market is the stock market [6], [7]. The proper forecasting and analysis of a stock index is significant in forming a trading strategy and management of portfolio risks [8], [9]. The nonlinearity inherent in financial data combined with its noise and time dependencies however restrict the efficacy of conventional econometric and statistical forecasting tools.

Conventional econometric models and classical machine-learning approaches often assume linearity or short-term dependencies, which restrict their ability to capture complex market dynamics and long-range temporal patterns.

In recent years, large language models (LLMs) have achieved great advancements, indicating their incredible accuracy in addressing complex tasks of natural language [10]. Recently, Transformer-based architecture and large language models (LLMs) have proven to have a high potential of extracting long-term dependencies via attention mechanisms which has led to a significant success in complex sequence modeling tasks [11], [12]. The variety of models that are paid by the flexibility of the LLMs allows them to be suitably adapted to a broad array of domain-specific uses, especially those related to economics and finance.

The financial industry has undergone digitalization contributing to the creation of large amounts of market data. Despite this abundance of data, existing forecasting approaches often focus on short-term horizons, employ computationally intensive Transformer models, or lack systematic feature engineering and leakage-aware preprocessing pipelines. Consequently, their scalability as well as their practical application, in actual financial systems, is constrained. This paper directly fills these gaps, suggesting a scalable hybrid financial forecasting system that is based on massive time-series feature engineering and a simple GAI-based Transformer architecture (ALBERT). In contrast to previous papers, the presented solution focuses on the efficiency of parameters, strong preprocessing, and structured performance comparison between the traditional machine-learning and deep-learning models. In this way, this study is expected to show that lightweight Transformer models possess the ability to produce high forecasting accuracy on large-scale financial time-series data without overly large computational burdens. To this end, the paper makes the following contributions to the literature on the topic of financial time-series prediction:

- Constructed a large-scale financial dataset based on historical S&P 500 data, comprising 200,000 records with price and volume attributes suitable for time-series forecasting.
- Developed a scalable end-to-end financial forecasting system that combines information preprocessing, feature engineering, model training and evaluation of large stock price predictions.
- Developed strong pre-processing and validation plans, such as time-ordered separation of data, deal with missing and infinite values, and Min-Max normalization, to avoid leakage of data and provide reproducible and trustworthy experimental outcomes.

- Extracted and engineered a diverse set of technical and temporal features, including RSI, MACD, Bollinger Bands, volatility measures, momentum indicators, and lag-based features, to enrich raw S&P 500 financial data.
- Used a lightweight Transformer-based architecture (ALBERT) to acquire complex temporal dependencies and contextual market patterns with the help of attention mechanisms.
- Performed an overall comparative analysis of forecasting performance on the basis of standard evaluation measures of RMSE, MAE, R^2 , and MAPE.

A. Justification and Novelty

This work is justified by the growing complexity, size and uncertainty of financial market that have posed a challenge to the performance of the traditional statistical and conventional machine learning based forecasting methods. Although the existing models cannot adequately represent nonlinear dynamics and long-term temporal dynamics, the given study proposes a new combination of structured financial time-series modeling and a lightweight GAI-based Transformer architecture. This is the main novelty: the model of ALBERT, a parameter-efficient Transformer, is applied to large-scale financial forecasting and has shown that it is possible to obtain high predictive accuracy without high computational constraints. Moreover, this research has added a comprehensive feature engineering plan and a strong, leakage-conscious preprocessing pipeline, which allows fast and reliable experimentation. This work empirically demonstrates the superiority of attention-based models to other conventional machine learning models like XGBoost and other traditional deep learning models by comparing ALBERT to them systematically. Taken together, these contributions move the state of financial time-series prediction forward and provide a scalable, practical, and data-driven forecasting model that can be used in real-life financial decision-making.

B. Structure of the Paper

The paper is structured as follows: Section II examines relevant literature, Section III outlines the suggested technique, Section IV talks about the analysis and outcomes of the experiment, and Section V wraps up the study with important conclusions and suggestions for further research.

II. LITERATURE REVIEW

This section reviews machine learning and generative AI models applied to personalized marketing and customer experience in e-commerce.

Nejabatbakhsh and Aliasgari (2026) enabled decentralized model training without sharing raw financial data, thus addressing privacy concerns in the financial domain. Experimental results in ten major technology companies (Tesla, Apple, Amazon, Microsoft, Google, etc.) demonstrate that the hybrid model achieves superior short-term forecasting performance, with an average R^2 variance score of 0.91 across ten major technology companies and a trend precision of 65.36 %, demonstrating strong prediction performance for short-term stock forecasting [13].

Deng (2025) introduced a method to separate cyclical trends from sudden disturbances using Fourier and residual analysis, enhancing sensitivity to anomalies. Experiments using CSI 300 enterprise data demonstrate that the proposed

framework outperforms ARIMA and LSTM in accuracy, achieving an RMSE of 4.70 in cash flow prediction, and surpasses traditional models in risk warning and path identification with up to 0.84 path similarity [14].

Zhao et al. (2025) explores the application of multi-head and self-attention mechanisms to further improve the model's representation capacity and forecasting performance. Validation on publicly available financial data, specifically Apple's stock prices from 2010 onwards, demonstrates that the attention-based model significantly outperforms traditional models. The values of MSE and MAE decreased by 15% and 12%, respectively [15].

Ho and Hung (2024) demonstrated using a financial time series dataset, specifically the 14-day horizon forecast of the S&P 500 index. The results showcase the effectiveness of the proposed approach, revealing a substantial improvement (up to 33.72%) compared to similar TFT models utilizing closing prices, classical EMD, and EEMD approaches. This machine learning framework has the potential to provide insights into forecasting financial data and to be broadly applicable across diverse fields of time-series forecasting [16].

Reddy et al. (2024) merged the analysis of time series using ARIMA with the machine learning method of Random Forest. The main objective of the research is to enhance the accuracy of market predictions in the face of constantly shifting market circumstances. The proposed model outperforms state-of-the-art models on a sample dataset. At RMSE 1.67, MAE 1.6, and MSE 2.8, it is rather effective. The model adequately accounts for a substantial portion of the variance, as shown by the R-squared value of 0.797 [17].

Fetrina, Utami and Arizki (2023) aimed to find out the results of the implementation of three types of Time Series analysis methods, namely Linear Trend Regression, Exponential Smoothing, and ARIMA on Bank Central Asia stock price index data for the 2020-2022 period and determine the method with the best accuracy level among the three methods. The results of this study indicate that the ARIMA (1,1,0) method produces the smallest RMSE value at 162.9544, so it has the best accuracy level among the three methods used [18].

Although Table I shows the financial time series forecasting has made a substantial development breakthrough, current research has a number of limitations. Most of the previous literature uses standard statistical models or composite machine learning methods that are not well poised to amplify the long-term nature of time dependencies and multifaceted nonlinear dynamics in the markets. Even though recent models based on attention and Transformer-based models have been improving in terms of performance, they can be heavy with regard to their computational needs or cannot be optimized in terms of their parameters, which cannot be deployed in practice. Moreover, the majority of the research is concentrated on short-term predictions or model-to-model comparisons and fails to present a systemic comparison between machine learning models and lightweight GAI-based Transformer architectures over large-scale financial data. Moreover, emphasis has not been laid so much on the strong feature engineering alongside leakage-conscious preprocessing pipelines to provide reproducibility and extrapolation under different market conditions. To fill these gaps, this research suggests an efficient and scalable financial forecasting framework that combines a large amount

of feature engineering with a sparse ALBERT-based Transformer model and compares it in detail with the known machine learning methods.

TABLE I. SUMMARY OF RELATED WORK ON FINANCIAL TIME SERIES FORECASTING MODELS

Author(s) & Year	Methodology / Model	Dataset	Key Results	Contribution
Nejatbakhsh & Aliasgari (2026)	Federated learning-based hybrid forecasting model	Stock data of major tech companies (Tesla, Apple, Amazon, Microsoft, Google)	Average $R^2 = 0.91$; trend precision = 65.36%	Enabled decentralized training while preserving data privacy and achieved strong short-term forecasting performance
Deng (2025)	Fourier transform and residual analysis with anomaly detection	CSI 300 enterprise cash flow data	RMSE = 4.70; path similarity up to 0.84	Improved anomaly sensitivity and outperformed ARIMA and LSTM in accuracy and risk warning
Zhao et al. (2025)	Multi-head self-attention-based forecasting model	Apple stock prices (2010 onward)	MSE $\downarrow$ 15%, MAE $\downarrow$ 12%	Demonstrated the effectiveness of attention mechanisms in enhancing forecasting accuracy
Ho & Hung (2024)	Machine learning framework with EMD-based decomposition	S&P 500 index (14-day forecast horizon)	Performance improvement up to 33.72%	Outperformed TFT models using closing prices, EMD, and EEMD approaches
Reddy et al. (2024)	Hybrid ARIMA and Random Forest model	Sample stock market dataset	MAE = 1.6, RMSE = 1.67, $R^2 = 0.797$	Improved prediction accuracy under dynamic market conditions
Fetrina et al. (2023)	Linear Trend Regression, Exponential Smoothing, ARIMA	Bank Central Asia stock index (2020–2022)	ARIMA (1,1,0) RMSE = 162.95	Identified ARIMA as the most accurate traditional time-series method

III. METHODOLOGY

The financial time series forecast is a structured methodology used in this study as exhibited in Fig. 1. The historical data of the S&P 500 are pretreated, normalized, and divided into time-ordered training and test sets. The feature engineering technique is utilized to derive technical and temporal features. XGBoost and ALBERT-based Transformer learns the complex temporal relationships through attention mechanisms. MAE, RMSE, R^2 and MAPE are utilized to assess model performance and the most accurate model is employed to forecast future prices.

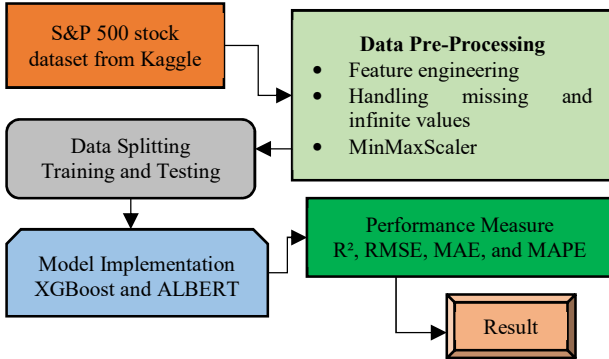


Fig. 1. Proposed Flowchart for Financial Forecasting.

A. Data Collection and Analysis

The dataset is the S&P 500 stock data¹ available on Kaggle which consists of historical stock price on the stock price index of S&P 500 companies. The dataset spans multiple years of daily trading records, covering long-term market trends and short-term price fluctuations, and contains 200,000 records and 7 attributes and has a shape of (200000, 7) comprising of date, price indicators, and trading volume, which is adequate to perform stock market analysis and predictive modeling.

Fig. 2 displays the correlation heatmap of the dataset's numerical characteristics. The price variables of open, high, low, and close have perfect positive correlations among themselves, which depicts a high level of multicollinearity in

these price variables. Conversely, the volume feature has a poor negative correlation (around -0.14) with all price characteristics, implying that there is a fairly independent correlation between trading volume and price changes.

Correlation Heatmap of Numerical Features

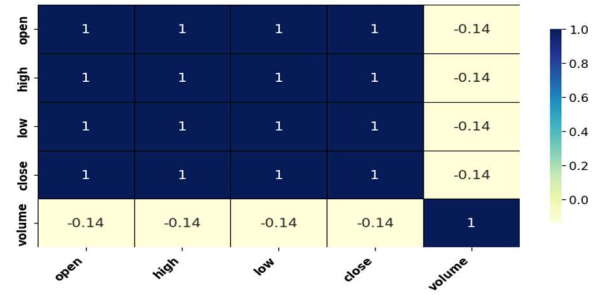


Fig. 2. Correlation Heatmap of Numerical Features.

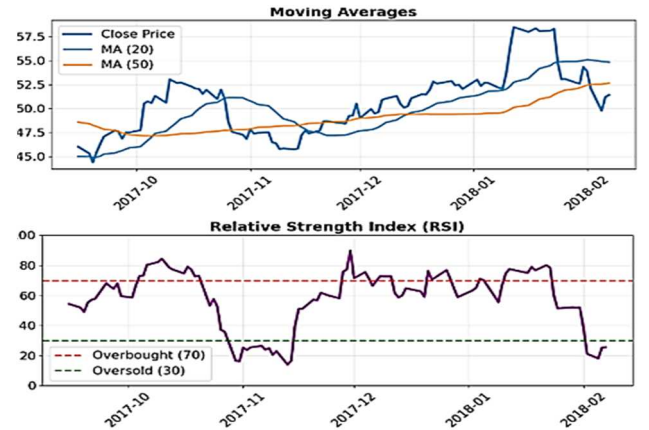


Fig. 3. Moving Averages and Relative Strength Index (RSI) Indicators.

Fig. 3 shows major technical indicators in the analysis like the MovingAverages and RSI. The top chart indicates the close price with the 20-day and 50-day moving averages, which indicate long-term price trends and short-term price trends and crossover points. The bottom plot puts the RSI, and the reference lines are used to denote the overbought and

¹ <https://www.kaggle.com/datasets/camnugent/sandp500/data>

oversold values (70 and 30 respectively), which assist in determining the changes in momentum and possible reversal points in the stock price dynamics.

B. Data Preprocessing

Data Preprocessing of data is a basic procedure of large-scale financial forecasting since it assures the quality of data and improves the performance of models. This step is elaborate feature engineering, smart missing value and infinite values, and correct data normalization to create clean, consistent and model-ready data in the context of advanced time series analysis.

1) Feature Engineering

The feature engineering aspect is an important step in the modeling process. The engineered features are technical indicators like the Moving Averages (20-day and 50-day), Relative Strength Index (RSI), Moving average convergence divergence (MACD), Bollinger bands, volatility measures, momentum indicators, volume-based features, and price lag-based features. Consequently, the dataset is further increased to 200,000 records having 22 feature variables which add substantial informational content towards making accurate forecast.

2) Handling Missing and Infinite Values

All the infinite values produced in the feature engineering are substituted with NaN, and all the records with NaN or infinite values are eliminated. Thus, invalid rows are removed (32651 rows) and the result is the clean and well-structured dataset that can be scaled and effectively modeled to make predictions.

3) Data Normalization Using Min-MaxScaler

Min-max normalization procedure is used in order to normalize the numerical features thus enhancing the performance of the entire model. This technique will make sure that the features are always scaled within a fixed range as shown in Equation (1).

$$y' = \frac{y - \min(y)}{\max(y) - \min(y)} \quad (1)$$

C. Data Splitting

It is split into 80:20, where the first 80 percent of time-ordered observations can be trained and the rest of the 20 percent are allocated to test, which does not allow any information leakage into the models during testing.

D. Proposed Models for Financial Forecasting

This paper combines XGBoost on structured financial time-series data with ALBERT on effective financial text analysis. It is combined to provide a GAI-based system that embraces both contextual market data and numerical pattern to forecast large-scale financial information.

1) XGBoost

The integration concept is used by the XGboost method, which can be applied to both regression and classification problems [19]. Essentially, the method finds the split node, builds the final model, and solves the minimal loss function using the integration notion and the second-order Taylor expansion. The method's foundational equation is as follows (2).

$$\hat{y}_i = \sum_k^k f_k(x_i) \quad (2)$$

A tree is represented by the additive function f_k in Equation (2), which is a tree ensemble model that predicts the

outcome using K additive functions. Hyperparameters such as the n estimators, maximum tree depth, and learning_rate are empirically tuned to balance prediction accuracy and generalization.

2) ALBERT

ALBERT, a streamlined language representation model, is designed for effective handling of text data in high-dimensional datasets [20]. It reduces memory usage and boosts processing speed, making it ideal for real-time financial data tasks such as sentiment analysis and evaluating the effects of market news. Mathematical Equation (3) for ALBERT.

$$H = \text{LayerNorm}(X + \text{Dropout}(W \cdot X + B)) \quad (3)$$

Where H is the hidden state, X is the input, W is the weight matrix, and b is the bias term. LayerNorm stabilizes training by normalizing the input. In this experiment, time-series data in numerical form are transformed into fixed length sliding windows, with each window being a sequence of normalized feature vectors of successive time steps. These sequences are embedded and fed into the ALBERT model whereby the self-attention mechanism learns temporal relationships over time. This is an adaptation that enables ALBERT to model numerical time-series data instead of textual input.

E. Performance Measure

Model evaluation is a very important process in which can determine the accuracy and generalization of the forecasting model based on statistical error measures in Equations (4) to (7). R^2 is utilized in measuring how well the prediction values are used in explaining the variation in real values, whereas RMSE and MAE are used to measure the magnitude of the prediction error. Also, MAPE measures the average error percentage of predictions in a percentage value, which is easier to interpret as a measure of forecasting performance.

$$R^2 = 1 - \frac{\sum_{i=1}^m (y_i - \hat{y}_i)^2}{\sum_{i=1}^m (y_i - \bar{y})^2} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^n (y_j - \hat{y}_j)^2} \quad (5)$$

$$MAE = \frac{1}{n} \sum_{j=1}^n |y_j - \hat{y}_j| \quad (6)$$

$$MAPE = \frac{100\%}{m} \sum_{i=1}^m \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (7)$$

In this case, n represents the overall count of observations, y_i denotes the real values, and $\hat{y}_i$ denotes the expected values. These measures of evaluation evaluate how different the results are between actual and anticipated and bigger errors are given more emphasis to make a reliable evaluation of the predictive performance of the model. Complementing RMSE, MAE has its transparent interpretation of average error that clearly evaluates the performance of a model. The model is then trained with the best hyperparameters after which final financial predictions are made on the test data. The analysis based on R^2 , RMSE, MAE, and MAPE shows that the model is accurate, strong, and can predict unforeseen data. All of these metrics show that the model is reliable for forecasting financial outcomes, which is helpful for making smart choices and having a solid financial plan.

IV. RESULT ANALYSIS AND DISCUSSION

The results were obtained using an experimental setup that included a 64 GB RAM stick, an NVIDIA RTX 3090 GPU with 24 GB VRAM, and two Intel Xeon 2687W v4 CPUs.

Standard regression based error measures are used to evaluate the forecasting performance of all the models and they include; the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and the percentage of error (mean absolute percentage error (MAPE)) that in combination are used to measure goodness of fit, the magnitude of an error and the relative accuracy of the prediction respectively. Table II compares the performance of XGBoost and ALBERT models using standard regression metrics. While XGBoost achieves competitive results ($R^2 = 0.9643$), ALBERT demonstrates superior performance with a higher R^2 of 0.9930 and significantly lower RMSE and MAE values. Overall, the results confirm the effectiveness of the ALBERT model for accurate and reliable large-scale financial forecasting.

TABLE II. EXPERIMENTAL RESULTS OF FORECASTING MODELS

Matrix	XGBoost	ALBERT
R^2	0.9643	0.9930
RMSE	21.5167	4.3021
MAE	3.1286	2.1380
MAPE	1.7148	2.9043

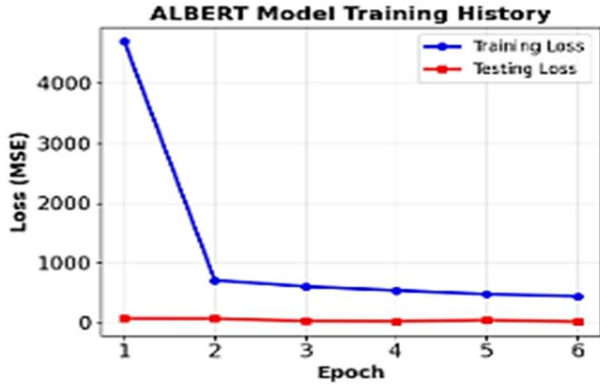


Fig. 4. Training and Testing Loss Curves of the ALBERT Mode.

Fig. 4 shows, in the context of MSE versus epoch, the training history of the ALBERT model. The training loss abruptly decreases in the first epochs, and then it decreases slowly, which proves the effective learning and the steady convergence. The testing loss is consistently small during the training process which indicates a high ability to generalize as well as insignificant overfitting the model.

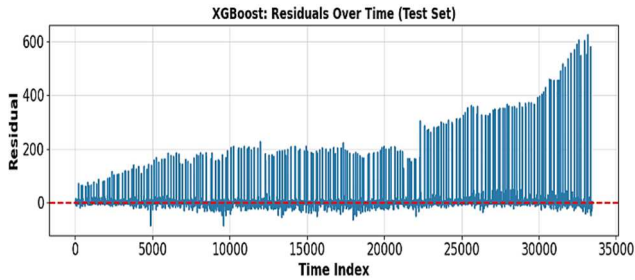


Fig. 5. Residuals Over Time for the XGBoost Model.

Fig. 5 shows the XGBoost model residual as the time passes through the test dataset. The residuals in the table are centered on zero and this means that the predictions are made unbiased in general, however, the value of the residuals are larger in the later time indices. This trend implies an increase in the error of prediction of larger stock prices and indicates the inaccuracy of the model to explain large changes in prices.

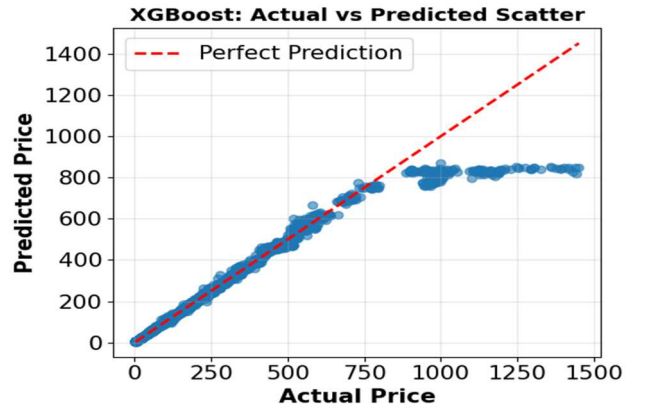


Fig. 6. Actual vs. Predicted Price Scatter Plot for the XGBoost Model.

The scatter plot of the XGBoost model's actual and forecasted pricing is shown in Fig. 6. There is a high forecast accuracy throughout a wide price range since the majority of the data points are around the ideal prediction line. Nevertheless, there are minor deviations at higher prices values indicating a lack of accuracy in the extreme price movement capture.

A. Comparison and Discussion

Table III demonstrates that there are distinct quantitative differences between the compared forecasting models. Though absolute metric values might vary owing to some variation in the dataset and experimental settings, this comparison brings out relative performance trends under similar evaluation criteria. The LSTM model has a high MAE of 58.01, which means that it cannot predict well. Conversely, XGBoost is better in terms of lower error rates (RMSE = 21.52, MAE = 3.13, and MAPE = 1.71). The ALBERT model has the lowest RMSE (4.30), which is the best measurement accuracy and strength of predicting the financial. Overall, the results show that the ALBERT-based approach is more effective than the traditional ML and DL models.

Residual analysis has indicated that XGBoost has greater error variance when prices change significantly whereas ALBERT has more consistent residuals hence more generalization and robustness. In general, ALBERT demonstrates the best RMSE, as well as MAE among all other compared models, proving that lightweight Transformer architectures are effective when it comes to large financial time-series forecasting.

TABLE III. COMPARATIVE PERFORMANCE ANALYSIS OF FINANCIAL FORECASTING MODELS

Model	RMSE	MAE	MAPE
XGBoost	21.5167	3.1286	1.7148
ALBERT	4.3021	2.1380	2.9043
RF [21]	0.00144	0.0244	-
LSTM [22]	-	58.01488	1.361079

This work shows how the potential of current machine learning and GAI models can be successfully applied to financial forecasting. Table III demonstrates that the proposed ALBERT model has been able to capture intricate market trends, as it has the lowest RMSE, and MAE, which is a key feature of the proposed model. XGBoost has also been shown to have a good predictive potential compared to traditional models like LSTM which have much higher error values which means that their predictive power is poor.

V. CONCLUSION AND FUTURE SCOPE

The accessibility of large datasets and major improvements in computation power has seen financial time series forecasting. The present work demonstrates that GAI-based Transformer models can effectively model nonlinear and complex temporal patterns in large-scale financial data. The given work has identified a high predictive potential of the ALBERT model that turns out to be the most effective among all the assessed models. Having the largest coefficient of determination ($R^2 = 0.9930$), and the smallest values of RMSE and MAE, ALBERT proves to be highly accurate and resilient in the process of complex, nonlinear financial market modeling and closely forecasting the real movements of prices. Despite some competitive results of XGBoost, the greater error rate of the model suggests that the model is not able to capture minute price changes. Conversely, predictive error of traditional deep-learning-based models like LSTM is significantly greater, which validates their lower viability in large-scale financial prediction. Altogether, the results indicate that lightweight Transformer models can also be used as a viable and efficient alternative in terms of financial time-series prediction when paired with strong feature engineering and preprocessing pipelines. Although promising, the study is restricted to historical data of the S&P 500, and the model performance might be subject to market volatility, and its generalization to other assets and markets is not proven. The limitations will be mitigated in the future through cross-asset generalization, integrating macroeconomic and news-based features and considering more complex architectures, including Temporal Fusion Transformers, GNN and reinforcement learning-based hybrid models.

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